

Flexible Design and Operation of a Smart Charging Microgrid

Vijitashwa Pandey
Oakland Univ.

Annette Skowronska
US Army TARDEC

Zissimos Mourelatos
Oakland Univ.

David Gorsich
US Army RDECOM

Matthew Castanier
US Army TARDEC

ABSTRACT

The reliability theory of repairable systems is vastly different from that of non-repairable systems. The authors have recently proposed a 'decision-based' framework to design and maintain repairable systems for optimal performance and reliability using a set of metrics such as minimum failure free period, number of failures in planning horizon (lifecycle), and cost. The optimal solution includes the initial design, the system maintenance throughout the planning horizon, and the protocol to operate the system. In this work, we extend this idea by incorporating flexibility and demonstrate our approach using a smart charging electric microgrid architecture. The flexibility is realized by allowing the architecture to change with time. Our approach "learns" the working characteristics of the microgrid. We use actual load and supply data over a short time to quantify the load and supply random processes and also establish the correlation between them. The quantified processes are then used to generate load and supply realizations over the long planning horizon. We show how this can reduce the computational effort when simulating microgrids for the entire planning horizon without impeding on their design under various operating scenarios considering uncertainty.

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1. INTRODUCTION

Microgrids are systems of interconnected sources and loads. If a microgrid is not connected to a major city utility, it is considered islanded where it is likely part of an emergency operation with a major utility not available [1]. While the best use of reliable microgrids is encountered in remote areas, including war zones, it is also at these locations that one must consider the implications of reliability. A reliable microgrid supports the loads with minimum service interruptions, with little fuel and component resupply and at a reasonable cost. Consequently, a microgrid system optimization problem involves multiple conflicting objectives. One objective is to maximize a measure of reliability which is defined as the ability of the online sources to power the online loads without turning them off unexpectedly. Other objectives include cost and the number of failures encountered within the planning horizon

(lifecycle). Because the microgrid is a repairable system (defined below), the classical notion of reliability is not directly applicable. For this reason, we use the Minimum Failure Free Period (MFFP) as a surrogate for reliability [1, 2, 3].

For repairable systems, the amount and frequency of repair affects how one perceives their reliability or more generally, their "performance." The classical notion of reliability, defined as the probability that the system has not failed before a given time t , can be misleading because a repairable system may have failed before time t and have been repaired [4]. The classical reliability definition can also impede decision making involving maintenance, availability and service cost of such systems. Although an appropriate maintenance strategy can make a system available most of the time, it cannot compensate for too many service interruptions and a

potentially high service cost. The tradeoffs between performance, service interruptions and cost are hard to capture. Pandey and Mourelatos [2] have recently shown that we can systematically approach the design and maintenance of repairable systems using a Minimal Set Of Metrics (MSOM) to capture most of the information about the working conditions and reparability of such systems. In this paper, we extend the methodology in [2] and apply it to a smart charging electric microgrid.

If a microgrid model is available, we can perform mathematical optimization over the discussed attributes. The optimization problem is generally set up as a non-linear mixed integer problem because of the non-linear objective function and the combination of discrete and continuous decision variables [5]. The power-load balance for the microgrid is managed by turning on and off sources and loads based on how much a load or source is above or below a required point (set points). There are other conditions as well such as the number of sources and loads, and inventory. The optimization problem can be solved using system simulations over a short time duration (e.g., hours) which requires extrapolation of results over the long planning horizon (e.g., one year), or by using a coarse time scale over the long time horizon. The former leads to a major disconnect between mathematical optimization and its actual implementation where the decision maker worries about long-term metrics such as Mean time Between Failures (MTBF) and cost, while computational issues guarantee that only short periods (or coarse time scales) can be simulated and hence optimized. As a result, one faces three issues:

1. **Incorrect extrapolations:** We must rely on extrapolations of results to consider the entire operating time which generally includes multiple years. Unless done properly, what is learned in a short simulation time may not be applicable to the entire planning horizon.
2. **Coarse time scales:** The simulation time intervals are too long. Many transient effects are not captured properly because they happen within seconds. A simulation using large time steps may miss these effects. The flip-side is that fine time scale simulations are computationally prohibitive.
3. **Uncertainty:** The effect of uncertainty cannot be fully captured. For example, we may encounter a chance failure and assume that the microgrid is unreliable or alternatively by luck, we may not see any failure in a short period even if the microgrid is unreliable.

The approach in this paper is different from classical approaches. It proposes “learning” from a short time operation and extrapolating to a longer period such as the planning horizon. The running protocol of a microgrid involves two elements - the total load the microgrid must service and the total supply it uses to service it. The “learning” we propose, refers to the random process of the overall load and the random process of the supply in response to the load. This ensures that the relative levels of load and supply are captured and the correlation between their evolutions in time is also

captured. Once the characteristics of load and supply are learned (i.e., their random processes are quantified), we can extrapolate them into the future to calculate long-term reliability metrics. This extrapolation is theoretically sound because it preserves the statistical characteristics of the load and supply processes as opposed to extrapolating the results of a short-time simulation. Short simulations are prone to missing extreme events and therefore, the relative frequency of events is likely to be miscalculated. Modeling of the entire process does away with this limitation.

As we show in [Section 2](#), a repairable system must be designed over multiple metrics that capture different facets of the system performance. We will show how to calculate the metrics of the system using a characterized (quantified) random process approach. Consequently, this work provides a framework to perform complicated analyses of microgrid operating scenarios. Remote systems have become more electrified over time and their power needs and generation capabilities have increased. Their optimal operation is therefore, critical. Available optimization methods using long-duration simulations are not however, practical because of the required computational effort. There are also many new concepts such as “gridable” vehicles that need to be analyzed. When vehicle systems link into other systems such as a microgrid in order to share power sources and loads, a vehicle-to-grid (V2G) system is formed [6]. Analysis of such microgrids is very complicated and a method that can extrapolate what is learned in a short time period can be very useful.

The paper is organized as follows. [Section 2](#) describes the proposed methodology and discusses a metric-based design approach of repairable systems using a minimal set of metrics and stochastic process modeling using time series. [Section 3](#) demonstrates the proposed methodology using a smart charging microgrid example. Finally, [Section 4](#) summarizes, concludes and discusses future research directions.

2. METHODOLOGY

2.1. Metric-Based Design of Repairable Systems

Classical reliability theory uses metrics such as the Mean Time Between Failures (MTBF) and availability to characterize the performance of a repairable system [4]. These metrics are calculated using times between failures and system repair frequency and durations. However, each of them captures only one statistic of the time to failure. The MTBF for example, captures the mean, while the availability is simply the ratio of system up-time to the total duration a system is in operation. A system that has a skewed distribution of the time between failures will not have its performance well represented by the MTBF or availability. To account for these limitations, we have proposed using a Minimal Set of Metrics (MSOM) to describe the performance of repairable systems [2]. The MSOM should be defined so that the metrics, individually or collectively, capture most aspects of the system performance. The reader is

referred to our previous work for a detailed description of the topic [2]. For the microgrid example in this paper, we use the metrics of cost (C), minimum failure free period with 80% probability ($T_{0.8}$), and number of failures (N_f) within the planning horizon. A Pareto front is generated over the metrics, which are then traded off by the decision maker to find the optimal combination that best satisfies his/her preferences.

2.2. Proposed Approach and Computational Issues

Microgrids contain many interconnected loads and sources. At each time, the running protocol decides, based on load requirements, how many sources to keep on, what capacity to run them at, and how much excess capacity to have in order to account for stochastic variations in load. Clearly, if we characterize the load random process and know therefore, its behavior through time, we can account for sudden load changes by suitably increasing or decreasing the supply. However, we cannot always do this perfectly because of inherent uncertainty in load and because of partial system failures. As mentioned earlier, the failures can be due to inadequate capacity to service the load or to actual subsystem failures. Cost considerations may also preclude a microgrid that never fails. Thus, failures are expected. For a dynamic system such as a microgrid, it is very difficult to predict its long term performance without actually simulating the grid for a long duration. Considering that most electrical transients happen in milliseconds, we need to run simulations with a very short time interval for months at a time in order to fully account for them. This is obviously computationally impractical.

We propose to “learn” the characteristics of the load profile $L(t)$ and the resulting supply profile $S(t)$, as enacted by an intelligent power management protocol. It is necessary to not only characterize the random processes $L(t)$ and $S(t)$ but also the correlation between them. This is because a supply that is not well correlated with load will either lead to many failures, wasted power, or both. A short period of a few days can be used for the “learning” process. Based on the quantified stochastic behavior, we can then extrapolate the two random processes for a long time (e.g., several months or even years) and record the number of failures where the supply is less than the load (Figure 1) and the times failures occurred. This information can be used to quantify the system performance metrics.

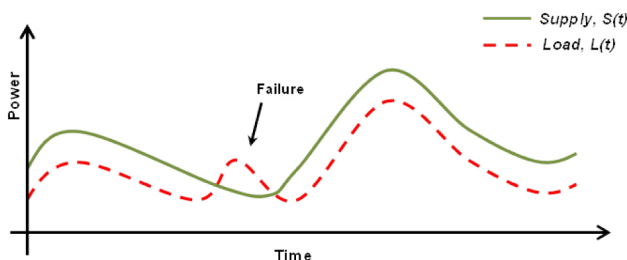


Figure 1. Realizations of the supply and load random processes

2.3. Overview of Time Series Modeling of Load and Supply Random Processes

We use a time series model to characterize the load and supply random processes. Time series models have been extensively used to characterize a random process [7]. They combine Auto-Regressive (AR) models, Integrated (I) models, and a Moving Average (MA) model. The Integrated (I) model is used if the process is non-stationary. All models use a feedback mechanism based on either past observations, past standard errors (MA), or a combination of the two, to determine future observations. AR models are the most commonly used. They provide a weighted average of past observations in addition to a white noise error term, to capture the correlation at instances t_1 and t_2 where $\tau = t_2 - t_1$ is small.

Consider a random process $X(t)$. A sample function $x(t)$ is discretized in the time interval $[0, T]$ using a uniform time step Δt so that $x_i = x(t_i)$ and $t_i = i \cdot \Delta t$. For a p order AR model, denoted as $AR(p)$, the discretized sample function is represented as

$$x_i - \mu = \phi_1(x_{i-1} - \mu) + \phi_2(x_{i-2} - \mu) + \dots + \phi_p(x_{i-p} - \mu) + \varepsilon_i \quad (1a)$$

where μ is the temporal mean of the process, $\varepsilon_i \equiv N(0, \sigma_e^2)$ is Gaussian white noise and $\phi_1, \phi_2, \dots, \phi_p$ are feedback parameters to be estimated. The above equation can also be used to create a derivative process as

$$y_i = \mu_i + L(x_i) \quad (1b)$$

where μ_i is the mean of the process $Y(t)$ at time i , x_i is a zero mean process modeled using the AR model of Equation (1a), and L is a function of x_i . To preserve stationarity of x_i after an existing trend is removed, L must be linear and μ_i constant.

After the feedback parameters are estimated in Equation (1a), a residual series $E(t) = X(t) - \hat{X}(t)$ is formed as the difference between the actual $X(t)$ and the estimated $\hat{X}(t)$ processes and statistical tests are performed to make sure that the random variables E_t and $E_{t+\tau}$ are uncorrelated for every τ . Details are provided in [7].

3. SMART CHARGING MICROGRID EXAMPLE

3.1. Essentials of a Microgrid and Design Details

A smart microgrid is used in remote locations to provide reliable power to critical installations. Microgrids incorporate intelligent power management to enable a robust and reliable